# A Hierarchical Model to Simulate Human Path Planning in an Environment with Discrete Footholds

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*Abstract*—**We studied human path planning in an environment where foot placement is allowed only on certain sectors arranged as distinct footholds. To study the underlying rules in human path planning, a set of experiments was designed in which six participants were asked to choose a path across the field of the distinct footholds without prior knowledge of the field arrangement once with normal and once with fast speed. Markers were attached on participants' ankles to record the foot trajectory. Qualitative analysis of the recorded data indicated that participants tend to preserve their initial orientation during the first two steps. During fast trials, footholds aligned with the line-of-progression were preferred by subjects, resulting in more steps with crossover. To study the logic applied in path planning, a hierarchical model was proposed to simulate human path planning in similar conditions based on the rules deduced from recorded data along with constraints depicting movement stability. Based on the results of analysis of the gaze data in [1], we assumed that at each step participants considered a sub-goal at two step-lengths ahead. Subsequently, location of the next step was determined inside the feasible area, reachable in a step, using the chosen sub-goal. This step should have the least deviation from the sub-goal line. Proposed model predicted 94% of trials successfully.**

***Index Terms*—discrete foot placement, navigation in a cluttered environment, hierarchical path planning, sub-goal selection.**

## I. Introduction

One may approach the subject of path planning from two different angles: human-like path planning, inspired by strategies employed by human for path finding [2], and methods focused mostly on optimization of the traverse length [3], computational cost [4,5], etc. The former approach leads to algorithms that can mimic human navigation, but does not necessarily result in minimization of the travel path or other cost functions. Main application of these algorithms is in path planning of biped robots, and in guidance of virtual animated characters (e.g. non-playable characters in video games, virtual actors, etc.) [2,5].

Analysis of human path planning methods has cleared that visual information is, indisputably, the most valuable data for path planning [6-8]. Identification of the environment, estimation of deviation from the goal line, extraction of information about obstacles, etc. are only possible by interpretation of visual information [7]. Furthermore, vision provides a feedback of current position of the body, which plays a critical role in maintaining stability during locomotion [8].

In addition to visual information, maintenance of dynamic and static stability and energy consumption are of high importance in human path planning. Another factor considered during path planning as concluded in [9] is that, when planning a path in cluttered environments, humans tend to minimize the difference between their orientation and goal direction (minimization of the directivity error). It is also stated that to preserve the dynamic stability, speed of progression must be taken into account when a path is being planned [10].

Bahrami and Patla, [11], have studied human path planning in an environment with disconnected footholds and proposed a fuzzy model to mimic human navigation. They suggested that individuals decide where the next foothold is located according to its reach-ability and angular deviation from the goal direction only one step ahead. To establish the reach-ability area, they assumed that, at each step, body orientation is determined from average direction of previous steps.

Results of gaze analysis during locomotion [1] revealed that human considers an area in about two steps ahead when planning a path. Since the fuzzy model in [11] does not comprise this feature, we developed a new model to incorporate the observed gaze behavior during path planning.

In this study a two-layer hierarchical model, inspired by [12], is developed to mimic human path planning across a field of randomly arranged disconnected footholds. The upper layer of the planner locates a sub-goal about two steps ahead and lower layer of the planner determines a foothold for the next step. In contrast to the proposed method in [11], we assumed that at each step, body orientation is determined by direction of the sub-goal which is chosen by the upper layer planner. To validate our model, paths resulted from simulation of the model are compared with the recorded paths from similar experimental conditions.

Section II gives information on the experimental setup, protocols and recorded data. Section III describes the hierarchical model. Results of the simulation and comparison to the recorded data are given in section IV. Discussion and conclusion on the results are provided in sections V and VI respectively.

## II. Method

24 plywood pieces were used to represent the isolated footholds in an area measured 4.55 m x 3.15 m. The footholds were randomly distributed on that area with the conditions that (1) no two footholds would have a common border or point, and (2) in front of each start and end point there must be a plywood foothold. Three different entrances and two different exits were determined. Five sets of randomly generated configurations for the footholds satisfying the two constraints were generated. Fig. 1 shows

one of the setups. Three entrances and two exits together with three configurations resulted in 60 different situations. Six healthy participants volunteered for the study. Each participant was guided to a start point with their eyes closed. They were told that after opening their eyes they have to start to go towards the specified end point. The participants were told to step only on the plywood footholds. Two infra-red markers were placed on the left and right ankles. Trajectories of the markers were collected by two OPTOTRAK camera sets. The markers on the ankles were used to record foot-placements.

## III. MODEL

We assumed that in a field of disconnected footholds, humans plan their path hierarchically, in two stages. The upper layer planner determines a sub-goal at each step, and lower layer planner chooses an appropriate sector for the next foot placement according to the selected sub-goal.

### A. *Reach-ability Area*

Reach-ability area represents the area that the swing foot can normally reach when the anatomical and stability constraints are considered. Since the model does not consider the geometric description of the body, the stability criteria integrated here define mainly static stability of the movement. Fig. 2 illustrates the reach-ability area. The area is defined by three parameters: maximum allowable anterior step lateral step length and width, respectively, and maximum allowable crossover angle. The model applies the reach-ability area to the field with reference to the direction of the sub-goal and support foot index, to identify sectors suitable for the next foot placement.

### B. *Upper Layer Planner*

In the upper layer a sector is determined as an optimum sub-goal by considering 1) its distance to goal, 2) its current stand point, and 3) its deviation from the goal line. Based on the results of analysis of the gaze data during human

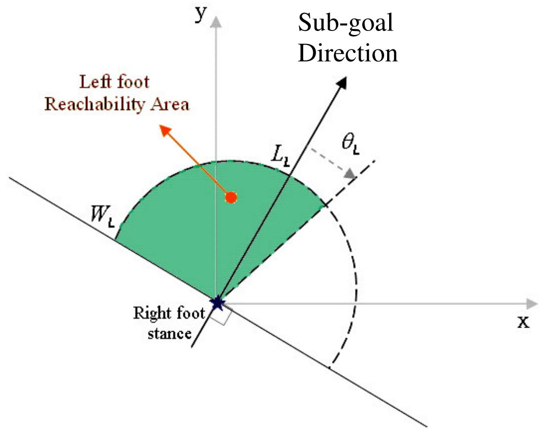


Fig. 2. Reach-ability area of the right foot, determined by maximum allowable step length, step width, crossover angle, and orientation of the model.

locomotion [1], we assumed that subjects consider sectors in the range of two step-lengths ahead; however, the exact range depends on the individual's attention. This uncertainty is incorporated into the model with parameter $\alpha$ such that $0.8<\alpha<1.1$. Therefore, upper layer planner first identifies sectors in the distance of $R$ where

$$L_L \text{ or } L_R < R < \alpha(L_L + L_R) \tag{1}$$

$L_L$ and $L_R$ represent left and right foot step length respectively. Consequently, three parameters are obtained for each sector: distance from current stance location ($R_i$), distance to goal ($R_g$) and deviation from the goal line ($R_d$). Consequently, for each foothold, a control parameter ($\eta_s$) is calculated as follow

$$\eta_s = \frac{R_i}{R_g \cdot R_d} \tag{2}$$

A foothold with maximum associated $\eta_s$ is selected as the sub-goal for current stance location. The procedure of sub-goal selection is illustrated in fig. 3.

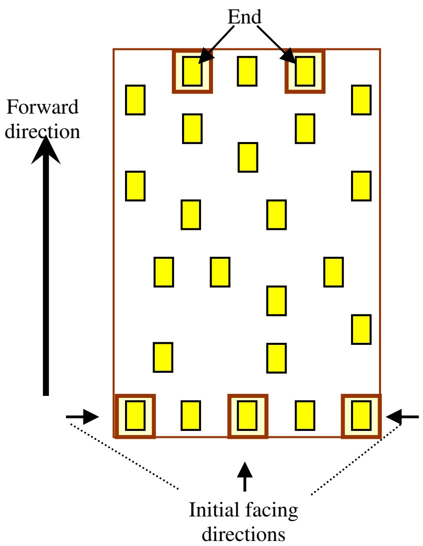


Fig. 1. Experiment Field; Filled blocks represent allowable footholds. Subjects start at one of the start points and choose their path through the field to one of the end points.

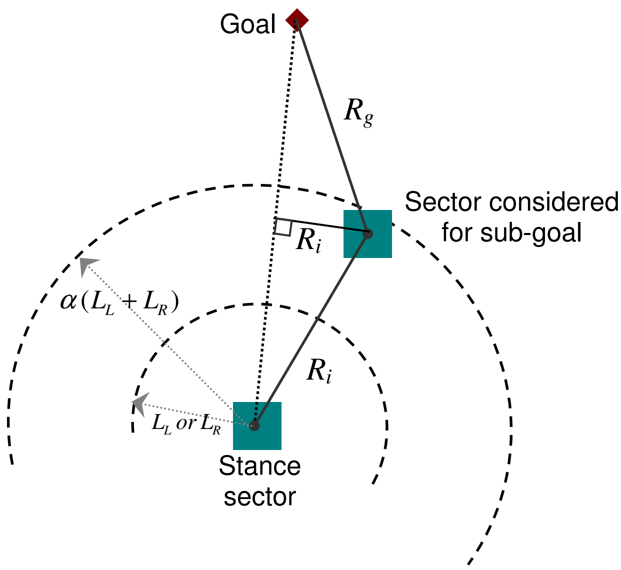


Fig. 3. The procedure of selecting a sub-goal. For all the footholds in the range of two step-lengths, ($L_L$ *or* $L_R$)< $R$ <$\alpha$($L_L$+ $L_R$), a control value $\eta_s$ is calculated.

### C. Lower Layer Planner

This layer determines a foothold for the next foot placement in the direction of the sub-goal. Based on the direction of the sub-goal, which is determined earlier, stability constraints (integrated in reachability area), and walking speed, lower layer planner determines a suitable foothold for the next foot placement. Three parameters are obtained for each foothold in the reach-ability area (similar to the procedure in III. *A.*): distance from the current stance location ($r_i$), distance to the sub-goal ($r_g$) and deviation from the sub-goal line ($r_d$). Consequently, for each foothold, a control parameter ($\eta_i$) is calculated as follow

$$\eta_i = \frac{r_i}{r_g \cdot r_d} \qquad (3)$$

A foothold with highest value for the control parameter ($\eta_i$) is the next foothold for the model. The process of sub-goal and foothold selection is repeated until the model reaches the goal.

## IV. Simulation Results

Model predicted accurately 57 out of 60 trials; the accuracy of the model for predicting recorded trials was 96% for normal speed and 92% for fast speed trials. In terms of subjects, model predicted the path taken by three subjects for both fast and normal speed with 100% accuracy. Table I shows the summary of success rate of the model for each subject at fast and normal speed.

From three trials which model failed to predict the recorded paths correctly, two were possible to be predicted correctly if the path were broken into two parts: once from the start point to a manually chosen mid-goal, and then from the mid-goal to the final goal. The third trial was different only in one foothold: the foothold in the recorded data required larger crossover than the one chosen by model. This might be explicable by taking dynamic stability of the subject into account. However, since the geometry of the body is not included in the model, therefore it ignores the dynamic stability of the movement. However, since the geometry of the body is not included in the model, therefore it ignores the dynamic stability of the movement. Fig. 4 displays both simulated and recorded path for this case. Crossover angle is also shown on the recorded data (Fig. 4-a); in contrast to the taken foothold by the participant, the model has chosen a foothold which requires no crossover at all.

Table II provides information on the amount of variation applied to parameters of the model for simulation of the 60

TABLE I
SUBJECT AND SPEED SPECIFIC SUCCESS RATE OF THE MODEL

| Success Rate | | | | | | | |
|---|---|---|---|---|---|---|---|
| Subject | 1 | 2 | 3 | 4 | 5 | 6 | all |
| Normal pace | 100% | 80% | 100% | 100% | 100% | 100% | 96% |
| Fast Pace | 100% | 100% | 80% | 80% | 100% | 100% | 92% |

TABLE II
MEAN VALUE OF THE PARAMETERS AND THEIR VARIATION FOR NORMAL AND FAST SPEED SIMULATIONS

| | Parameter | Mean | Standard Deviation |
|---|---|---|---|
| Normal Speed | Max. Step Length, $L$ | 102.5 | ±5.333 |
| | Max. Crossover angle, $\theta$ | 30° | ±0 |
| | $\alpha$ | 0.8833 | ±0.0379 |
| Fast Speed | Max. Step Length, $L$ | 112.67 | ±8.172 |
| | Max. Crossover angle, $\theta$ | 28.333° | ±6.477 |
| | $\alpha$ | 0.8833 | ±0.0379 |

trials. These variations can be interpreted as variations in subjects' anthropometric parameters, different physical experience backgrounds, etc.

## V. Discussion

As mentioned in section III, simulation of the model in 6% of the trials resulted in paths which in some footholds were different from the recorded paths. The differences were mainly at the start of the path and just before reaching the goal. It was observed that some subjects tend to maintain their initial orientation at the start of the path (for the first two steps), almost regardless of the goal direction. A similar characteristic was observed in normal human walking towards a specific target [2]. This behavior was integrated into the model by using normalized weighted sum of sub-goal direction and subject's initial orientation for the first two steps. A similar characteristic was observed when participants took the last step to reach the goal. To determine the last foothold, most subjects took into account their body orientation only at the last step, without considering the exact location of the goal. By maintaining the orientation at the last step, model was able to select the last foothold correctly.

The effect of traveling speed is integrated into the model by penalizing sideward stepping and giving bonus to the footholds in the plane of progression.

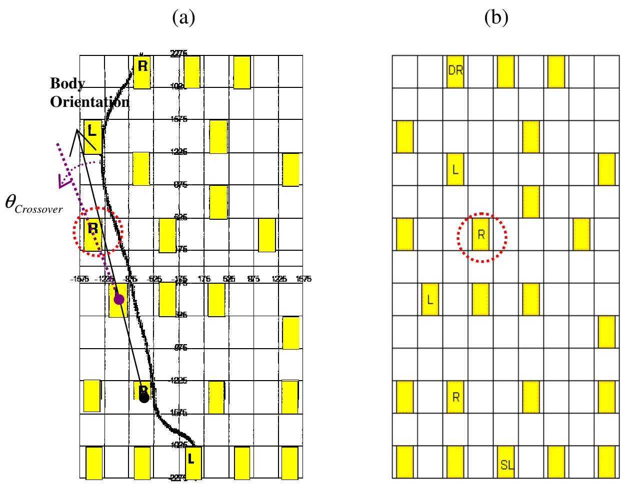


Fig. 4. A case which model failed to mimic the recorded path. (a) Recorde path, and (b) the result of simulation.

## VI. Conclusion

The model proposed here predicted the paths taken by human subjects with the accuracy of 94% over the fast and normal speed trials. This supports the assumptions made in developing the model such as sub-goal detection in two step-lengths ahead, maintaining directivity towards goal, maintaining initial body orientation for the first two steps of the path, choosing longer steps during fast trials, and preferring steps with the least amount of crossover. Results from the model suggest that similar rules may be employed by human for path planning in an environment with disconnected footholds.

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